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ORIGINAL ARTICLE

Assessing the role of reward in task selection using a reward-based voluntary task switching paradigm

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Abstract People exhibit a remarkable ability to both maintain controlled focus on executing a single task and flexibly shift between executing several tasks. Researchers studying human multitasking have traditionally focused on the cognitive control mechanisms that allow for such stable and flexible task execution, but there has been a recent interest in how cognitive control mechanisms drive the decision of task selection. The present research operationalizes a foraging analogy to investigate what factors drive the decision to either exploit task repetitions or explore task switches. A novel paradigm—reward-based voluntary task switching—ascribes point values to tasks where the overall goal is to accumulate points as quickly as possible. The reward structure generally rewards switching tasks, thereby juxtaposing the motivation to gain increased reward (by exploring task switches) against the motivation to perform quickly (by exploiting task repetitions). Results suggest that people are highly sensitive to changes in both reward and effort demands when making task selections, and that the task selection process is efficient and flexible. We argue that a cost–benefit mechanism might underlie decisions in multitasking contexts, whereby people compute task selections based on both the reward available for selecting a task and the effort necessary to execute a task.

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Introduction

Choosing between tasks is a vital component of human multitasking. People are faced with a vast array of tasks throughout daily life, and it is often of one's own volition to decide how time and effort are allocated among such tasks. Yet the decision processes underlying task selection during multitasking have only recently become a topic of scientific inquiry. The rich research literature on multitasking has traditionally focused on structural and functional limitations of the control mechanisms recruited to execute and switch among tasks. Task performance is guided by the activation of a task set, or that specific collection of cognitive operations (i.e., perception, attention, memory, decision, and motor response) recruited to execute a given task (Logan & Gordon, 2001; Meiran, 2000; Yeung & Monsell, 2003). Performing two tasks in an interleaved fashion requires task sets to be sequentially activated and inhibited, which is manifested in slowed performance on task switches compared to task repetitions, or the so-called switch costs (Rogers & Monsell, 1995). One core goal in this domain has been to precisely define the mechanisms that operate upon task sets to avoid relinquishing the explanatory burden to the dreaded homunculus, or an unexplained source of intelligence in the system (for a review, see Botvinick & Cohen, 2014). In contrast, the present research focuses on the choice processes underlying task selection during multitasking, with a specific emphasis on how rewards associated with each task may interact with cognitive control mechanisms needed to complete task execution. The study builds on recent work investigating the procedural aspects of cognitive control on one hand and the motivational aspects on the other hand to develop a new experimental paradigm within which questions of task selection may be addressed.

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Voluntary task switching

Within the task switching literature, one research paradigm that has facilitated the consideration of the integration of choice processes and cognitive control is voluntary task switching (VTS; Arrington & Logan, 2004, 2005). Like other task switching paradigms, VTS involves the sequential presentation of a series of bivalent target displays that support the performance of two tasks. Unlike other task switching paradigms that use cues or predetermined task orders, participants are instructed to select a task to perform on each trial, generally under global instructions to perform the tasks in a random order. Participants must therefore select which task to perform and then the appropriate response for that task. In some variants of the procedure, a first response indicates the task selection and a second response provides the categorization judgment based on the selected task and presented stimulus. More commonly a single response is used to capture both the task selection and task performance measures. In VTS, task performance measures of response time (RT) and accuracy show performance switch costs that are largely consistent with other task switching paradigms. The slower and less accurate performance on switch trails likely reflects added cognitive operations needed to shift task sets, or overcome interference from a previous task set (for review see Kiesel, et al., 2010; Vandierendonck, Liefooghe, & Verbruggen, 2010). More importantly, VTS allows for the direct consideration of task selection, either in terms of the task performed on a given trial or the transitions between tasks, or switch probability. One key behavioral finding in terms of task selection is a repetition bias, by which participants fail to switch at the proportion (0.5) appropriate for the instructions to switch at random. Research using the VTS paradigm has uncovered a variety of factors that influence the magnitude of this repetition bias, including bottom-up effects such as stimulus repetitions (Mayr & Bell, 2006), stimulus availability (Arrington, 2008), stimulus identity (Arrington, Weaver, & Pauker, 2010) and task strength (Yeung, 2010), as well as top-down effects such as preparation time (Arrington & Logan, 2005) and concurrent working memory load (Demanet, Verbruggen, Liefooghe, & Vandierendonck, 2010). For a recent comprehensive review, see Arrington, Reiman, and Weaver (2014).

One of the outstanding questions about the use of the VTS paradigm to study mechanisms of task selection is that of how participants are making selections on a trial-by-trial basis within the context of the global experiment-wise instructions regarding task selection (Arrington, et al., 2014). Stemming from the initial VTS paper (Arrington & Logan, 2004), instructions to participants in VTS studies often include statements that tasks should be performed "in a random order" or "unpredictably" resulting in the bar for ideal behavior being a 0.5 switch proportion overall. Thus, instructions to perform randomly provide the context in which trial-by-trial task selection occurs, as well as the basis for two accounts of the task selection processes in VTS (Arrington & Logan, 2005; Vandierendonck, Demanet, Liefooghe, & Verbruggen, 2012) that both include assumptions about how individuals represent a random sequence of events. The instruction to perform tasks randomly is an experimental manipulation intended to elicit both task repetitions and switches, but is unlikely to reflect the way in which most human multitasking environments are approached. Several recent studies have manipulated global instructions to examine the influence on task selection processes (Kessler, Shencar, & Meiran, 2009; Liefooghe, Demanet, & Vandierendonck, 2010). Generally, as the constraints of the global instructions decrease (e.g. from "randomly," to "equally often," to no instructions), the probability of switching decreases, though the magnitude of this decrease depends in part on what tasks are being performed (Arrington, et al., 2014). This systematic manipulation of the global instructions demonstrates the importance of context on task selection, but these instructions remain far from the sorts of constraints that operate on task selection in real-world multitasking. To begin to understand the task selection processes that are involved in more real-world settings, we turn to the literature that more closely investigates the motivational aspects surrounding the recruitment of cognitive control.

Motivation and cognitive control

The emphasis in the cognitive control literature has recently shifted from investigating the constraints on controlled processing to investigating the motivational aspects underlying the recruitment of control (Inzlicht & Schmeichel, 2012). One such approach is the hierarchical reinforcement learning (HRL; Botvinick, Niv, & Barto, 2009) framework, which draws from the vast literature on reinforcement learning (for a review, see Dayan & Niv, 2008) to propose that deployment of cognitive control can be organized into two general levels of abstraction: lower level, procedural processes (termed actions), and higher level, goal-driven processes (termed options). While the literature on basic reinforcement learning demonstrates that individuals readily learn basic stimulus–response reward contingencies at action levels, the HRL account further proposes that reward contingencies can be learned at option levels of abstraction that include the goal state as well as the set of actions that support reaching that goal. The HRL framework provides accounts for activity in the anterior cingulate cortex (ACC; Holroyd & Yeung, 2011) and has recently been elaborated in a computational model (Holroyd & McClure, 2015). While the full review of the neural and computational data is beyond the scope of this paper, the HRL model includes the concept of task sets, making the HRL framework particularly relevant to thinking about how task selection might function in VTS. Within this model, task sets are thought to be synonymous with or be represented at the level of options (Botvinick et al., 2009; Holroyd & McClure, 2015). The mechanisms that are responsible for making task selections are also responsible for maintaining task set activation, and may be mediated by the same areas of the brain, though there is disagreement over whether such control of task sets resides in the ACC (Holroyd & McClure, 2015) or dorsolateral prefrontal cortex (DLPFC; Botvinick, et al., 2009). In either case, the placement of task-set maintenance near the top of a control hierarchy (relative to procedural execution) is also in line with long-standing theories of control and task performances (Cohen, Dunbar & McClelland, 1990; Gilbert & Shallice, 2002; Miller & Cohen, 2001). Furthermore, if mechanisms of task set maintenance overlap with those of task selection, then task selection should be influenced by the activated task set.

Related perspectives building on the reinforcement learning approach have focused more directly on the inputs to the task selection mechanism by asserting that a cost–benefit mechanism drives task selections by computing the expected value of control (EVC; Shenhav, Botvinick, & Cohen, 2013). The EVC mechanism generally computes the expected value of an array of options that can be performed, and determines both which task should be performed and how much control should be applied to the task (i.e., the "identity" and "intensity" of the control signal; see also Westbrook & Braver, 2016). Because recruiting control is intrinsically costly (Kool, McGuire, Rosen, & Botvinick, 2010; Kool & Botvinick, 2014; Kurzban, Duckworth, Kable, & Myers, 2013; Westbrook, Kester, & Braver, 2013), one of the primary functions of the cost–benefit mechanism is to efficiently optimize the expected utility of effort allocation—one does not wish to work harder than one needs to achieve a reward. Thus, there are three major parameters that factor into task selection: resources to be gained and lost (e.g., money), the probability of gaining or losing resources, and the amount of control, or effort, necessary to execute the task (for recent reviews, see Kool, Shenhav, & Botvinick, 2017; Shenhav et al., 2017). This account further implies the prediction that control becomes increasingly costly as it is exerted for a longer period of time. Sustained performance on harder tasks necessitates more reward as a function of time on task, suggesting that effort becomes more subjectively "costly" as it is exerted (Kool & Botvinick, 2014). The question of why control is costly is quite complicated and controversial (for an extensive review, see Shenhav et al., 2017), but for the purposes of the HRL theory, the EVC theory, and the present research, the key observation is that control *is* costly.

Consider a cost–benefit mechanism underlying allocation of cognitive control during task selection within a VTS paradigm. The most basic result of task switching is the switch cost that occurs when transitioning from one task to the next. The repetition bias seen in standard VTS paradigms (Arrington & Logan, 2004) may reflect some avoidance of the effort cost associated with switching. It is possible that the effort cost of switching is being weighed against the benefit of making a sequence more random. While compelling, this interpretation does not arise from an experimental environment wherein a cost–benefit mechanism of task selection in VTS can be quantified.

The present research

To this end, we introduce a new reward-based voluntary task switching paradigm,[1] which associates points with task selection to create a global context that encourages coordinating task selection and task execution to maximize points. Points (ranging from 0 to 10) are designated for each task, and on every trial participants know how many points will be received for correct performance of each task. The overarching goal is to reach 500 points as quickly as possible. The reward structure is designed with a foraging analogy operationalized in the following manner: From trial to trial, point values for the task that were previously performed have a 0.5 probability of decreasing by one. Point values for the previously unperformed task have a 0.5 probability of increasing by one. Thus, the basic design of the reward structure is a 2×2 factorial design in which the points associated with the current task (defined as the task performed on the previous trial, indicating that the task set for that task should be currently activated at the start of a trial) may either remain constant or change, decreasing by one, and the points associated with the other task (defined as the task not performed on the previous trial) may remain constant or change, increasing by one. The trial-by-trial changes in points are probabilistic and manipulated independently for the two tasks. The point-based reward structure that favors switching is set in direct opposition to the effort associated with performing a task

[1] While Fröber and Dreisbach (2016), among others, have implemented reward for task execution during VTS, to our knowledge, rVTS is a novel approach in that it is the first to implement rewards for task selection in a VTS environment.

switch, thus allowing for quantification of any cost–benefit calculations underlying task selection in VTS. Using this new paradigm, we address two questions about how reward information is incorporated into task selection in multitask environments.

The first question addresses how reward information in reward-based voluntary task switching (rVTS) is linked to or incorporated within the task set representation that supports task execution. As noted above, a task set refers to that set of cognitive operations, or subordinate processes, that are required to perform a task (Logan & Gordon, 2001; Meiran, 2000; Yeung & Monsell, 2003). While not generally thought of as including reward information, some approaches suggest this is possible. For example, Botvinick and Braver (2015) describe the task set as including "action-outcome contingencies" and Hommel and colleagues have long considered how action effects help mold task performance (e.g. Hommel, 2009). The HRL and EVC frameworks differ regarding the directionality of influence between option selection and task-set maintenance. The HRL account suggests that the "option" level of the hierarchy is responsible for both choosing the appropriate option and maintaining the task set appropriate for executing the option (Holroyd & McClure, 2015). The EVC account considers the task selection and maintenance functions to be dissociable and their relationship unidirectional: an option selection mechanism integrates costs and benefits of various options to manufacture a "control signal" consisting of the identity of the task to perform and how intensely it should be performed. This control signal is then transmitted to separate mechanisms responsible for maintaining the appropriate task set and procedurally executing the task (Shenhav et al., 2013). In the current design, we address this question by considering whether participants show different degrees of sensitivity to point changes for the current task value versus the other task value. Point values for each task were presented in a consistent, spatially compatible location to promote binding of the reward information to the related task. While the specific reward values changed slowly across trials, a spatial location for where the reward information can be accessed remained constant throughout the experiment. If task-set activation includes activation of the current reward information through biasing processing of the information at that location, then performing a task might lead towards heightened sensitivity to that task's value.

The second question addresses how to quantify a cost–benefit mechanism that might underlie selection in a VTS context. The rVTS reward structure allows us to directly quantify the benefit for a task switch. Given a scenario where both tasks are worth the same number of points, the most efficient approach is to repeat the task, thus avoiding the performance cost associated with switching. However, as the points for the other task value increase relative to the current task value, the balance between conserving effort and maximizing points shifts. We will consider the nature of this shift by examining the point difference between the two tasks where participants are equally likely to switch or to repeat tasks, the so-called indifference point. The magnitude of the indifference point may reveal how great the "cost" is for the effort required to switch—this approach draws from behavioral economic approaches that have recently gained popularity in the literature on motivation and cognitive control (Westbrook & Braver, 2015; Westbrook et al., 2013). Furthermore, we anticipate that this cost may vary as a function of time, where effort becomes more costly as effort has been expended for a longer period of time (Kool & Botvinick, 2014). We predict that the indifference point will increase as the experiment progresses. This would suggest that as participants expend more effort throughout the course of the experiment, the "cost" of effort increases, and participants will demand more reward for the effort and time cost associated with a task switch.

Method

Participants

Seventy-three participants were recruited from Lehigh University and took part in this experiment for optional course credit. All participants had normal or corrected-to-normal vision and color vision. Ten participants were dropped due to error rates greater than 15%, suggestive of a failure to maintain focus on the tasks. This left 63 participants for final analysis.

Stimuli, tasks, and procedure

Two simple identification tasks were performed on colored shapes. The stimuli varied in terms of color (red or blue) and shape (circle or triangle). The targets appeared in the center of the display and were 2 cm by 2 cm. Participants were instructed to judge either the color or shape of the target on each trial. Responses were mapped to the "D", "F", "J", and "K" keys and constrained such that two possible responses for a single task were mapped to one hand (e.g., "red" and "blue" might be mapped to "D" and "F" requiring responses from the middle and index fingers of the left hand). The response keys were counterbalanced across participants.

Digits representing the point values for each task appeared approximately 2 cm to the left and right of the target. Point values were aligned with the tasks mapped to the left and right hands. The digits ranged from 0 to 10 and represented the number of points participants would

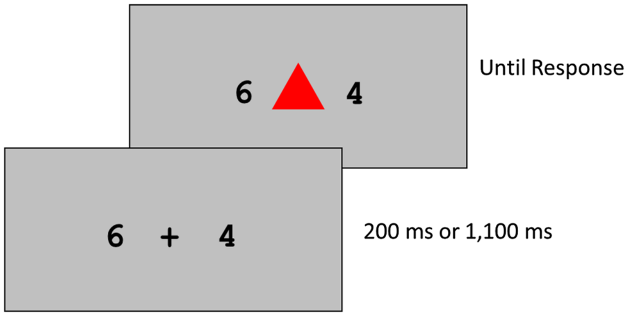

Fig. 1 Reward-based voluntary task switching trial sequence. Trials began with a display of the task point values updated from the previous trial to reflect the points available for the performance of each task on the current trial. After either 200 or 1100 ms the target stimulus appeared and remained on the screen until the participant responded

receive for accurate performance of that task. At the beginning of each block, both task values were set to five points each. After participants made a task selection, there was a 0.5 probability that the current task value would decrease by one point. Meanwhile, there was an independent 0.5 probability that the other task value would increase by one point. The color of the font changed to indicate how the task value had transitioned from the previous trial—black for constant, red for decreased, and green for increased.

At the beginning of each trial, the points would appear on the screen for either 200 ms or 1100 ms, after which the target stimulus appeared and remained on the screen until the participant gave a response (see Fig. 1). For incorrect responses the word "error" appeared on the screen for 500 ms, after which the trial sequence repeated. Each block ended when participants reached 500 points. Following the block, the finishing time was displayed on the screen; participants were encouraged to complete each block as quickly as possible. The session began with instructions for each task and participants performed single task practice blocks of 16 trials. They then completed task switching practice within two short 16-trial blocks of cued task switching to familiarize them with both switching and repeating tasks and the effort associated with each task transition. Participants were informed of the reward structure and told to try to develop a strategy of responding that they thought would work best. Participants then practiced 16 trials of rVTS, followed by performing 12 blocks of rVTS for data collection.[2]

[2] Participants also completed the behavioral inhibition/activation system questionnaire (BIS/BAS; Carver & White, 1994), with the idea being that reward sensitivity might predict behavior in rVTS. We also collected age and gender demographic information. However, none of these factors proved to be significant predictors of task selections in rVTS and are not included in the analyses presented here.

Design

The core design of the experiment was a 2 × 2 factorial based on the point value transitions associated with each task. For the variable current task value, the levels were constant, indicating that the point value had not changed from the previous trial, and decrease, indicating that the point value decreased by one point from the previous trial. For the variable other task value, the levels were constant, indicating that the point value had not changed from the previous trial, and increase, indicating that the point value increased by one point from the previous trial.

Results

Data trimming and coding

The initial data handling involved trimming the first trial of each block, error trials, and the trials following error trials, resulting in the removal of 13% of the data. For RT analyses, outliers were trimmed on a participant-wise basis, such that observations more extreme than plus or minus two standard deviations from each participant's mean RT were removed, resulting in a removal of 3% of the data. Trials were coded as task repetitions if the task performed on trial n was the same as the task performed on trial $n - 1$ and task switches if the task performed changed from trial n to trial $n - 1$. The point difference variable was coded as the current task value subtracted from the other task value. Thus, positive point differences indicate that the other task value is greater than the current task value.

Individual differences in measures of selection and performance

One important contribution of the current study is the introduction of a new paradigm, rVTS, for examining the impact of task value on multitasking. As with any new paradigm, it is useful to document the range of response patterns shown by participants. Figure 2 provides descriptive statistics, histograms, and correlations for five measures, representing different aspects of task selection and performance. Switch proportion captures aspects of task selection that represent general tendencies of participants' task sequences. Reward sensitivity is calculated at the mean switch proportion on trials where both current task value and other task value change (representing the largest value transition possible) minus trials where both current task value and other task value remain constant (representing no value transition). The reward sensitivity is intended to capture the individual's responsiveness to changes in the task values on a trial-by-trial basis. The

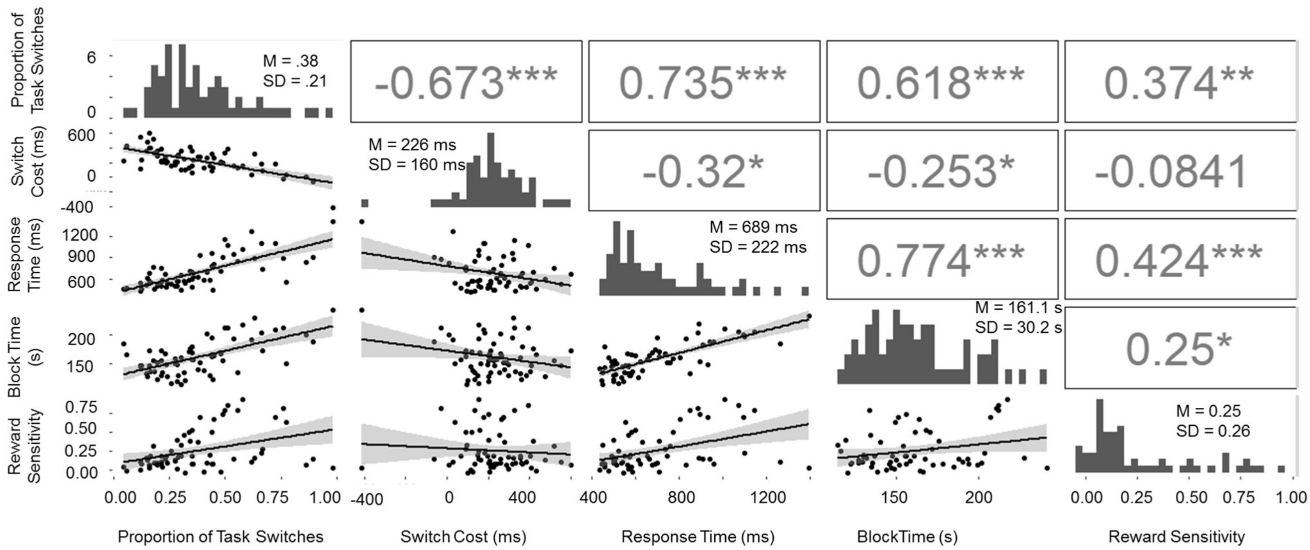

Fig. 2 Distributions of and correlations between individual difference measures in rVTS. Reward sensitivity reflects the switch rate when both tasks change value minus the switch rate when both task values are constant

overall RT, switch costs, and block time variables each serve as measures of task performance, with block time indicating how efficiently the participants met the overall instructions to reach 500 points as quickly as possible.

Task performance

To confirm that task performance followed typical patterns seen in task switching experiments, we analyzed task RT using a 2 (RSI 200 or 1100 ms) × 2 (transition: repetition or switch) within-subjects ANOVA. Two participants were excluded from the analysis because of missing cells in the design: one participant never switched tasks at short RSIs and the other never repeated tasks at short RSIs. There was a main effect of RSI [$F(1, 59) = 54.77$, $p < .001$, $\eta_p^2 = .48$], indicating that RTs were slower at short RSIs ($M_{short\ RSI} = 821$ ms, SE = 38 ms) than at long RSIs ($M_{long\ RSI} = 739$ ms, SE = 28 ms). There was also a main effect of transition [$F(1, 59) = 121.07$, $p < .001$, $\eta_p^2 = .67$], indicating that RTs were faster for repetitions ($M_{repetition} = 689$ ms, SE = 29 ms) than for switches ($M_{switch} = 994$ ms, SE = 37 ms). There was a significant interaction between RSI and transition [$F(1, 59) = 90.82$, $p < .001$, $\eta_p^2 = .61$]. Following up on this interaction revealed that switch costs were larger at short RSIs [$M_{repeat} = 717$ ms, SE = 35 ms; $M_{switch} = 1158$ ms, SE = 40 ms; $F(1, 59) = 730.32$, $p < .001$, $\eta_p^2 = 0.93$], than at long RSIs [$M_{repeat} = 661$ ms, SE = 26 ms; $M_{switch} = 882$ ms, SE = 35 ms; $F(1, 59) = 183.52$, $p < .001$, $\eta_p^2 = 0.76$]. These results demonstrate the performance cost associated with switching tasks and replicate the common finding in task switching that switch costs are greater at shorter, rather than longer, RSIs (Arrington & Logan, 2005).

Task selection

For the present purposes, the focus of the main analyses is on the processes of task selection with the primary dependent measure of mean switch proportion. The first analysis addresses the question of whether task set activation influences sensitivity to task value through looking at the effect of transitions for the current task value vs. the other task value. The second analysis explores the nature of the cost–benefit analysis performed by participants by calculating the indifference point and examining how it changes over time throughout the experiment.

Task values for current and other tasks

Figure 3 provides the mean switch proportions as a function of current task value transition and other task value transition. The impact of the task point values on task selection was assessed in a 2 (current task value: constant or decrease) × 2 (other task value: constant or increase) within-subjects ANOVA on the proportion of task switches. There was a main effect of current task value, indicating that switch rates were significantly higher when the current task value decreased by a point ($M = .42$, SE = .03) than when it remained constant [$M = .32$, SE = .02; $F(1, 32) = 49.11$, $p < .001$, $\eta_p^2 = .44$]. There was also a main effect of other task value, indicating that switch rates were significantly higher when the other task value increased by a point ($M = .45$, SE = .03) than when it remained constant [$M = .29$, SE = .02; $F(1, 62) = 67.28$, $p < .001$, $\eta_p^2 = .52$]. There was also a significant interaction between current task value and other task value [$F(1, 62) = 6.69$, $p < .001$, $\eta_p^2 = .28$].

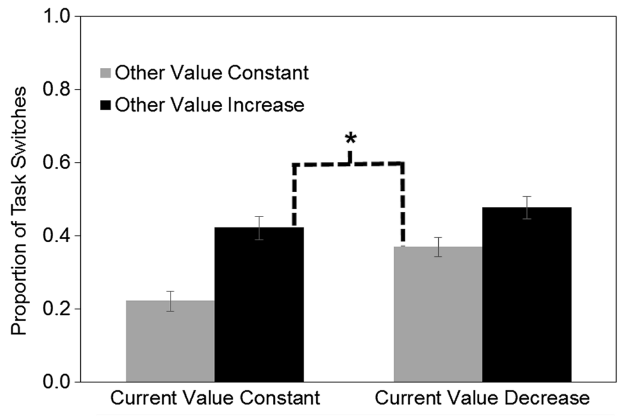

Fig. 3 Mean switching proportion by reward condition. Constant indicates that the point value has remained the same from the previous trial. Other value increase indicates that the other task value has increased by a point from the previous trial, while current value decrease indicates that the current task value has decreased by a point from the previous trial. Error bars reflect standard errors. *$p < .05$

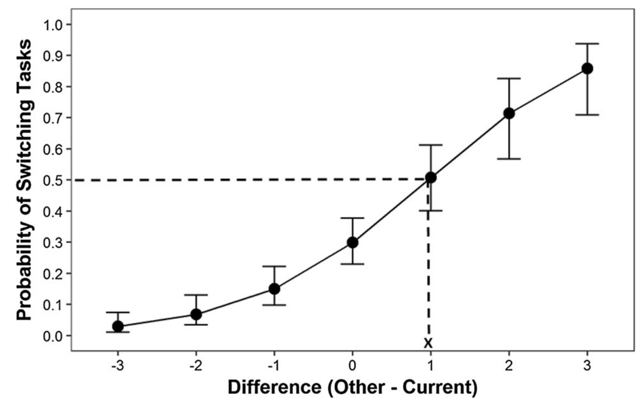

Fig. 4 Main effect of point difference on the probability of switching, as predicted by the generalized linear mixed model. Higher values of the point difference indicate the extent to which the other task value was greater than that of the current task. The "X" marks the indifference point, where participants are equally likely to switch as they are to repeat, which equals 0.94. Error bars represent 95% confidence intervals generated from the mixed model

Critically—and in contrast to our prediction—switch rates were significantly higher when the other task value increased by a point while the current task value remained constant ($M = .42$, SE = .03) than when the current task value decreased by a point while the other task value remained constant [$M = .37$, SE = .03; $F_{\text{contrast}}(1, 62) = 15.25$, $p < .001$, $\eta_p^2 = .20$].

Point difference and block

The benefit of switching tasks can be quantified through consideration of the point difference between the current and other task values. While the possible range of values for the point difference is from -10 to 10, the majority of trials fell in the range of -3 to 3. The distribution of observations of point difference showed a steep decline at the more extreme point difference values and resulted in a large number of participants with missing cells of data. These trials were trimmed prior to this analysis, resulting in the removal of 31% of the data. The point difference variable was used to estimate the indifference point, or that point difference between the current and other task values where a participant was equally likely to repeat or switch tasks. The block variable was centered at block six to allow the model to generate estimates across data from the middle portion of the experiment.

The mean switch proportions were analyzed as a function of point difference and block in a generalized linear mixed model using the lme4 package (Bates, Maechler, Bolker, & Walker, 2015) in R (R Development Core Team, 2017). Because generalized linear mixed models were fit to these data, it is important to note that the effects reported below and the corresponding figures are predictions generated from the models. By fitting a linear model to these data, we extrapolated predictions across unobserved levels of the point difference variable when making inferences about how the indifference point changes as a function of various factors in the design. Odds ratios are reported in text, and where appropriate are converted to probabilities for displaying in Fig. 4. Observed means are reported in the text to corroborate the predicted effects from the linear models.

There was a main effect of point difference (plotted in Fig. 4), indicating that a point increase in the point difference in favor of the other task value was associated with a 2.44 factor increase in the odds of switching ($p < .001$). This main effect suggests that participants are indeed able to monitor the values of the tasks, and tend to choose the task that is of greater value. The observed means support this prediction from the model, where the probability of switching is lower when the current task value is three points greater than the other task value ($M = .20$, SE = .03) than when the current task value is three points less than the other task value ($M = .49$, SE = .04).

The intercept of the model is 0.43, meaning that—when the tasks are of equal value, and during the middle of the experiment—the odds of repeating are greater than the odds of switching tasks. The marginal mean of switch proportions when the point difference equals zero reaffirms the model's prediction that there will be a repetition bias when the tasks are of equal value ($M = .35$, SE = .04), in line with other VTS studies (Arrington & Logan, 2004). Further, the model predicts that the indifference point is 0.94, meaning that the odds of switching are equal to that of repeating when the other task value is about one point greater than the current task value (see Fig. 4). This supports our prediction that the indifference point would occur when the other task value is greater than the current task value, suggesting that reward is needed to offset the cost of switching between tasks.

There was a main effect of block ($\beta = 0.94$, $p = .004$), indicating that as the experiment progressed, each subsequent block was associated with a 0.94 factor decrease in the odds of switching, specifically when there was zero point difference between tasks. Because the likelihood of switching decreased uniformly throughout the experiment, it suggests that the cost of switching increases as effort is expended for a longer period of time, and thus more reward may be needed to offset the effort cost before deciding to switch tasks. This intuition is supported by the calculated indifference point increasing monotonically throughout the experiment from 0.62 points in the first block to 1.35 points by the final block (see Fig. 4), and it is also supported by the fact that mean switch proportions were higher in block 1 ($M = .43$, SE = .03) than in block 12 ($M = .30$, SE = .04).

There was also a two-way interaction between point difference and block ($\beta = 0.97$, $p = .03$). To follow up on this interaction, the model was rerun with the point difference centered at +3 (other task value three points higher than current task value) and −3 (vice versa) to observe the impact of block on the likelihood of switching at both extremes of the point difference. This approach revealed that when the value of the other task was three points greater than that of the current, each increase in block reduced the odds of switching by a factor of 0.88 ($\beta = 0.88$, $p = .001$). However, when the value of the current task was three points greater than that of the other task, the odds of switching did not significantly vary across blocks ($\beta = 1.06$, $p = .17$). This interpretation is supported by the observed means of switch proportions, where the difference in switch rates between the first and last blocks when the difference was -3 was smaller ($M_{\mathrm{FirstBlock}} = .23$, SE = .06; $M_{\mathrm{LastBlock}} = .16$, SE = .06) than when the difference was +3 ($M_{\mathrm{FirstBlock}} = .51$, SE = .05; $M_{\mathrm{LastBlock}} = .35$, SE = .05).

Discussion

Emerging perspectives—such as the EVC theory—have only recently begun attempting to explain the mechanisms underlying the motivated allocation of cognitive control as governed by a cost–benefit mechanism. Since theories surrounding such cost–benefit mechanisms are largely in their infancy, one of the major objectives in developing such theories is to find supporting evidence across domains, including voluntary action selection (for a review, see Kool et al., 2017). The present study sought to investigate two major aims with respect to motivation and cognitive control in rVTS: (1) to what extent does activation of task set influence or include representation of task reward, and (2) are selections in rVTS likely to be driven by a cost–benefit mechanism? The data revealed that the active task set did influence choices, and on the whole, a cost–benefit account of control allocation provides a parsimonious explanation for selections in rVTS.

Task set and task selection

If reward information is linked to or incorporated with the task set that supports task execution, we predicted that there should be increased sensitivity to the value of the current task, leading to a bias to switch more in response to decreases in the current task value rather than increases in the other task value. While a bias was indeed present in the data, it was opposite to our expectation—switch rates were higher in response to increases in the other task value, rather than to decreases in that of the current.

The bias towards increased sensitivity to other task value adds nuance to a larger picture of how information is accumulated to inform choices. The EVC and HRL theories largely deal with the value-comparison stage of the decision process—once all values (i.e., costs and benefits) are on the table, how can the system parse this information to drive action selection (for an overview of the decision-making framework, see Rangel, Camerer, & Montague, 2008)? But these results highlight a potential mechanism by which value information is brought to the table. In rVTS, participants faced a context where the expected utility of a task switch was constant across two cells of the design, the only difference being whether the current task value decreased from the previous trial or that of the other task increased. If the process of acquiring value information was identical across the two tasks, switch rates should not have differed across these two cells of the design. But instead we observed greater sensitivity to changes in the value of the non-previously performed task. It is conceivable that lingering task set activation might have consequences for subsequent selection processes—much like lingering task set activation has consequences for subsequent execution processes (Yeung, 2010). However, the direction of the effect is opposite of what would be predicted if the activated task set led to greater consideration of the current task value. The increased sensitivity to the other task value is also opposite of what would be predicted if participants were acting in a loss-averse fashion (Kahneman & Tvsersky, 1979). The change in points for the current task value involved a loss of available points as opposed to an increase in available points for the other task.[3] If participants

[3] We stress that, in rVTS, participants only ever faced possible reductions to prospective gains and never true loss of their acquired resources (i.e., points); the latter is the true conception of "loss" invoked by prospect theory (Kahneman & Tversky, 1979).

responded based on principles of loss aversion, we might predict greater switching when the current task value changed.

One potential explanation for the direction of the choice bias involves a role of visual attention in task selection. On trials where only one of the values changed—because values were continually presented on the screen—the visual discontinuity created by the change in point value may have created a type of "flicker" effect, drawing attention to the task for which the reward has changed (Yantis & Jonides, 1990). Evidence accumulation models of decision making and visual attention posit that fixating an option results in accumulation of more evidence for that option, thereby increasing preference for choosing said option (for a review, see Orquin & Loose, 2013). The current results suggest that attention to the task values, rather than just target stimuli, may have a similar effect. This effect would be akin to a mere exposure effect (Zajonc, 2001) where looking at the values associated with a task might engender a preference to select that task. In the case of attending to the current task value, this would increase the likelihood of a task repetition; whereas in the case of attending to the other task value, this would increase the likelihood of a task switch—just the pattern seen in the current data. Pilot eye-tracking data from our laboratory suggest that first fixations to task values are indeed predictive of the task selection in just this fashion.

Costs, benefits, and multitasking

In rVTS points directly tied to each task quantified the benefit associated with performing each task. The cost in terms of increased effort and RTs associated with a task switch can thus be considered in light of this benefit. Participants demonstrated sensitivity to both effort and value associated with tasks and transitions when making task selections, as evidenced by the main effect of point difference and the average indifference point being greater than zero. These results also revealed that the cost of effort increases as more effort is expended, as seen in the main effect of block, indicating that the likelihood of switching decreases as participants progress through the experiment, as well as in the increasing indifference point across blocks.

The finding of a positive indifference point is generally supportive of the EVC and HRL theories (Holroyd & McClure, 2015; Shenhav et al., 2013). People construe effort as a cost that discounts gains and are thus motivated to utilize effort as efficiently as possible. This view is in line with recent evidence suggesting that effort is only expended insofar as it ensures the receipt of reward, and more effortful "types" of control are recruited depending on the demands for securing reward (Kool, Gershman, & Cushman, 2017). The finding that the indifference point increased over time is also in line with evidence suggesting that effort becomes more costly the longer it is expended (Kool & Botvinick, 2014). These findings add support to the idea that the repetition bias observed in VTS is indeed a form of effort avoidance (Arrington & Logan, 2004), and rVTS has the unique advantage of leveraging behavioral economic tools to more quantitatively assess effort aversion in voluntary switching contexts. Future research should continue to investigate the process surrounding voluntary effort investment, and we echo the claims of others by urging researchers to utilize paradigms capable of revealing subjective costs of effort across individuals (Westbrook & Braver, 2015; Westbrook et al., 2013).

Conclusion

Within the broad context of a special issue on human multitasking, we have presented a consideration of the mechanisms of task selection, which is often overlooked in task switching and other dual task procedures. We worked from an assumption drawn from the broader task switching literature that behavioral switch costs are reflective of cognitive effort required to reconfigure the cognitive system to perform a new task and/or overcome interference from a previously activated task set, although our consideration of task selection is currently neutral as to the exact nature of this effort. With the introduction of the rVTS paradigm, we provided a new tool for the examination of task selection mechanisms. Using a reward structure that operationalizes a foraging analogy, we were able to address the question of how individuals balance the competing forces of minimizing cognitive control effort and behavioral switch costs and of maximizing reward. We conceptualize this balance as a cost–benefit approach that efficiently integrates rewards and effort costs and that shifts as a result of prolonged effort. Moving forward, a unified understanding of human multitasking must consider not only the mechanisms of and limitations to task execution during multitasking, but also the mechanisms involved in task selection and the interactions among selection and execution mechanisms.

Compliance with ethical standards

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Conflict of interest We declare no conflicts of interest in the conduct or reporting on the present research. We agree to make raw data available if requested.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. The protocols for these experiments were approved by the Lehigh University Institutional Review Board.

Informed consent Informed consent was obtained from all individual participants included in the study.

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